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A Hybrid Method for Measuring Service Supply Chain Performance Management in IT Service Providers

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***Abstract*—Despite the increasing development of research in the service supply chain, the IT service supply chain measurements have not grown proportionally. In this paper, based on a survey the key indicators in the IT service supply chain and ranking them, a new hybrid method for measuring the supply chain performance in IT service providers is presented. IT services are examined in three subcategories: Customer Relationship Management (CRM), Supplier Relationship Management (SRM) and Mutual Trust. In this method, comparative vectors in the high dimension space using the AHP method are developed from relationships between effective IT service supply chain factors and the Kernel LS-SVM method is presented for outranking. The Kernel LS-SVM method allows the presentation of mean surface and provides a hyperplane for outranking. The result shows that knowledge and skills, management information system, security service management system, ability to communicate effectively with the customer, ability to establish effective relationships with suppliers, performance of provided services and customer response time, criteria are the highest importance among 112 examined indicators and More attention to them caused an significant increase in quality of measuring the performance of companies.**

Keywords-Service Supply Chain, Performance Measurement (SSCPM), Kernels SVM, Ranking AHP Information, Technology Service

I. INTRODUCTION

The service has a significant part of Gross Domestic Productivity (GDP) among countries, even in BRICS developing countries (30.4% to 87.2%) [1, 2]. It has been increasing rapidly in recent years, accounting for 65.042% of world GDP in 2019. There are also numerous predictions that services will account for a significant fraction of the world economy [3]. Therefore, examining the service supply chain along the product supply chain is an essential research area. The service supply chain is divided into two categories: Service Only Supply Chains (SOSCs) and Product Service Supply Chains (PSCs). SOSCs are supply chain systems in which the "products" are pure services, and there are no physical products. For example, in many service industries, such as psychological counseling, financial services, and even IT services, supply chains are SOSC. In contrast, a majority part of the service supply chain is in the form

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of PSCs, in which services and "physical products" are present simultaneously [4].

One of the definitions provided for SOSC is a "network of suppliers, service providers, consumers, and other supporting units that perform the functions of transactions of resources required to produce services. Transformation of these resources into supporting, core service, and the delivery of these services to customers" [5]. In contrast, PSSCs (more general than SOSC) are the first models and frameworks for defining a service supply chain introduced by Ellram et al. [6] in 2004. In this framework, the service supply chain defines as "The management of information, processes, capacity, service performance, and funds from the earliest supplier to the ultimate customer" ". In other words, the service supply chain can introduce as a network consisting of suppliers, service providers, consumers, and other service production units that create the resources needed to produce the service, convert resources into support services, as well as deliver these services to customers [5].

The unique characteristics of the service supply chain compared to the product's supply chain can be listed as intangibility, heterogeneity, inseparability, perishability, customer participation, and difficulty of quality dimension evaluation [7]. Wang and his colleagues Develop a framework of service supply chain performance measurement. Based on the strategic, tactical, and operational level performance in a service supply chain, measures and metrics are discussed.

Recently, the measurements are proposed to measure, rank, and select services which are proposed in researches such as Providing Service Chain Measurement Scales [8], and Service Supply Stability Measurement Frameworks [9]. Due to the increasing role of services and IT services in the supply chain, it has become particularly more prominent than before. Presenting the measurement methods in information systems [10, 11] has created a framework for managing this chain. Examining the service chain framework of information systems created a regular structure in this area [12]. Besides, services in the field of information systems and information technology are of great importance. In this paper we look at the information system services and offer a new method to create a measure based on Machine learning. However, the various table text styles are provided.

II. RELATED WORK

Service supply chain performance measurement

Service features include tangibility, inseparability, and heterogeneity, making it difficult to measure service chain performance [13]. Also, uncertain and qualitative criteria for services are challenging to measure. Ambiguity in the definition of services in new technologies such as IT services are other problems that make evaluating the performance of the service supply chain a challenge [14]. According to the methods of previous studies related to the performance of the service supply chain, the areas under consideration are divided into the following nine main groups: Production processes, human resources, logistics, information technology, theory and model generation, productivity and profitability, environmentally friendly practices, customer satisfaction, and other cross-disciplinary studies [15].

For this purpose, it is important to provide frameworks for evaluating the performance of the service supply chain, which is defined according to the diversity of the service part.

We present the frameworks and measurement criteria based on previous related research, which illustrated in Table 1. In this paper, we focus on the sample of the IT service supply chain. Due to the significant spread of IT services, it considers an important challenge. The contribution of IT services in world Trade Organization projects in recent years has approximately reached 21% of world trade and predict to increase to 25% by 2030 [16]. Therefore, improving productivity in the parts that produce ICT services is directly contributes to the productivity of the whole economy [17]. In recent years, work on IT service models has expanded. In the area of provision of service supply chain frameworks and the considered sample in measuring the performance of the service supply chain, we can point to [18]. Also, in the area of digital services, Social Commerce Platforms Services, we mention to [19], offshore IT services [20], and Cloud service [21].

In this paper, we consider the general framework in IT services created in the previous research based on the Meta Synthesis method, CASP method, and Logical model. We also use combining SVM-ranking and AHP methods to measure the performance of the service supply chain. A vector machine (SVM) is a linear system in a high dimensional feature space, which learns a linear function by a learning algorithm based on optimization to create a classification or regression [22]. Vapnik introduced the first model of SVM [23] due to its excellent performance, which has been considered in many areas such as random learning, pattern classification, regression, and computer vision. The kernel is a method used to improve SVM. When a linear system couldn't separate data in the data space, we need to map the data to the projection space to use SVM [24]. We use SVM to create an overall ranking among the alternatives in the supply chain index.

Performance measurement based on machine-learning approach

Machine learning and MCDM methods have become a method to manage the supply chain and service supply chain in recent years. AI technologies can cope better with complexity and uncertainty than "traditional methods". Because it is designed to be more like the human functioning decision [39].

A. AHP METHOD

The AHP method was developed by [40] to determine the relative importance of a set of activities in a multi-criteria decision problem. This method makes it possible to judge intangible quality criteria along with tangible quantitative criteria [41].

The AHP method consists of three parts: Problem hierarchy structuring, Pairwise comparisons of the alternatives, Synthesis of the priorities.

AHP converts a complex MCDM problem into a hierarchy of decision elements (criteria, decision alternatives) in the first step. There are at least three levels of hierarchy: the overall goal of the above problem, multiple criteria at the intermediate level, and alternatives of the decision at the lowest level. In the second step, we compare pairwise the alternatives of each criterion in the middle level, which leads to the creation of comparative matrices related to the alternatives of each criterion. In the last step, we will reach the weights of the alternatives using the linear composition of the largest eigenvectors of comparative matrices [42]. Table 1: Shows the sample of the IT service supply chain.

B. LEARNING METHOD

As yet, many learning methods have been proposed in the area of provider selection, such as support vector machine combined with decision tree [39] and overall performance of providers based on BLR-RT-NN [43]. Also, supply chain trust diagnosis (SCTD) service using the Bayesian network approach [44] and the decision tree method for the provider in the reference [45]. We should point out that selection will have less computational complexity than AHP. Moreover, hybrid methods to manage of optimization, multi-input, and multi-output optimization for managing the supply chain, which provides a solution to study the supply chain [46]. In the reference [47], the measurements checked the relation between the learning algorithm and MCDM methods. It is essential to mention that learning methods could benefit more data space than MCDM methods.

Providing measurements and performances for the services chain of a ranking structure for alternatives is a problem studied in recent years. Using machine learning algorithms has been considered for creating frameworks for outranking. For this purpose, the reference [48] proposed the ML-PL method to rank a set of alternatives. Also, we can point to the PCA method in [49] presented a multi-criteria rating methodology. The main disadvantage of the AHP is that the values given by the decision-makers are subjective. According to this fact, the reference [50] develops a method to rank the DMUs by applying the DEA (Data envelopment analysis “LP”) and AHP models.

C. SVM METHOD

Among the various machine learning methods, SVM-based methods have found many applications in addition to MCDM methods. Among the ten machine learning algorithms in the supply chain management, SVM method has the following characteristic [51]:

1. *Suitable for nonlinear classification*
2. *Applicable both to classification and regression*
3. *Easy to explain*
4. *Fewer generalization errors*
5. *Sensitive to kernel functions and parameters*

To study the provider’s performance management based on DEA, and SVM we can consider the reference [52]. Lina proposed an influence analysis method of top management team and investment efficiency by using SVM [53]. Furthermore, we can study the microenterprise credit criteria model using SVM and R-type clustering in the reference [54]. L2 regularization SVM performs well to model a customer-provider relationship analyzed in [55]. Providing a less computational method or complexity for consuming the design of experiments (DOE) by SVM is provided in [56].

In the matter of provider evaluation and selection, artificial intelligence approaches obtained better performance than conventional methods in evaluating the providers’ performance and determining the best providers. This Model is statistically powerful and studied in MLP, ANFIS, SVM [57]. The SVM and TOPSIS-cd-based methods investigated to select the best cloud service supplies, which provides a more appropriate outranking than the TOPSIS method [58]. LS-SVM weighted kernel-based method used AHP for feature weights in feature ranking and feature selection problems [59]. Besides, provider selection and evaluation and estimate performance rating of supplier selection and evaluation problem [60, 61] proposed by LS-SVM provide a good result. We use the SVM-Ranking method that creating a platform for ranking, and web screws were presented based on user clicks in 2002 [62]. This article aims to provide the most important criteria for performance evaluation of the service supply chain in IT. Here we take advantage of the framework presented in our previous work [64]. We present a new method based on the learning machine to rank the chain criteria of IT services so that the most important criteria of this field are extracted from the one-level framework.

In Section 3, we will overview the required methods to introduce the AHP Kernel LS-SVM Ranking algorithm. We will analyze and simulate the method on the criteria framework using the opinions of experts. In the end, method results and the FAHP method will be compared.

Here we extend the SVM Ranking method so that in a one-level mode without the need for alternatives criteria to have a suitable vector space for applying the SVM algorithm. The results show that our method not only is faster than the FAHP outranking method but fulfills the expectations that we have from the expert observations to present the most important IT criteria. Finally, we identify the most important criteria of the IT service supply chain.

TABLE I. SAMPLE OF THE IT SERVICE SUPPLY CHAIN.

REFRENCESE	Methods	Case study	Performance measurement
Lai and Cheng [25]	importance-performance analysis(IPA)	The transport logistics industry in Hong Kong	Service effectiveness for shippers (SES), Operational efficiency for transport logistics service providers (OE), Service effectiveness for consignees (SEC)
Ellram et al. [6]	Supply Chain Operations Reference (SCOR) model		Capacity Management, Demand Management, Customer Relationship Management, Supplier Relationship Management, Service Delivery Management, Cash Flow Management
Sahay et al. [26]	gap analysis methodology, Data envelopment analysis (DEA)	3PL service provider	Logistics Users (LU), Logistics Service Providers (LSP) (between Supplier and the Focal Firm, between the Focal Firm and the Distributor, between Distributor and the Customer)
Sengupta et al. [27]	FACTOR ANALYSIS	Industry sectors for service companies	Information sharing, Product and service customization, Long-term relationships, Hedging strategy
Baltacioglu et al. [5]	SCOR model and Ellram et al. models.	healthcare industry	demand management, capacity and resources management, customer relationship management, supplier relationship management, order process management and service performance management
Gaiardelli et al. [28]		Italian automobile and motorcycle manufacturers in the premium sector, manufacturer of cooking appliances	business level(financial results, market, cost, customer satisfaction, flexibility, productivity), activity level (reliability, responsiveness, internal lead times, waste and costs, asset utilization), development and innovation level (service portfolio, a human resource, it and service capacity)
Yang et al. [29]	structural equation modeling (SEM), Confirmatory factor analysis, resource-based view (RBV)	Taiwanese container shipping service	Service quality, Customer satisfaction, Customer loyalty, Profit rate, Market share, Sales growth rate, Return on investment, Reduced operation cost
Arlbjørn et al. [30]	lean practices	Danish municipalities	Ellram et al.
Giannakis [31]	SCOR model	rail transport service	Competitiveness, Financial performance, Flexibility, Resource utilization, Innovation, Quality of service.
Boon-itt and Pongpanarat [32]	Q-Sort		Ellram et al.
Cho et al. [13]	fuzzy analytic hierarchy process	Hotel supply chain	Service supply chain operation, Customer service, Corporate management
Kindström and Kowalkowski [33	synthesizing research process	Swedish Government Agency	Offering, Revenue model, Development process, Sales process, Delivery process, Customer relationships, Value network, Culture.
Boon-Itt et al. [8]	Q-sort	Thai service industries	process capability in: Supplier relationship management , Service performance management , IT management , Order process management , Customer relationship management , Demand management , Capacity and resource management.
Pandari and Azar [34]	fuzzy cognitive mapping (FCM)		Service-delivery management, Supplier-relationship management Customer-relationship management, Market management, Service-capability management, Knowledge- and information-flow management, Cash-flow management, Risk management
Yuen and Van Thai [35]	SCOR model	manufacturers and shipping companies in Singapore	Operational Performance (Flexibility, Quality, Cost, Delivery)
Tseng et al. [9]	Fuzzy Delphi Method and Analytical Network Process	electronics manufacturing firms in Taiwan	Reverse logistic integration in service package; Collaborative planning, forecasting, and replenishment with suppliers ; Customer service innovation program ; Total supply chain cycle time ; Reduced service costs
Leksono et al. [36]	DEMATEL, balanced scorecard (BSC)		Operational costs, ROI,Profit,Total Revenue,Efficiency, Quality of service, ROA, Delivery Time, Flexibility, Level of inventory, Cost of TIC, Capacity of TIC, Human resources, Qualification and competency, HRD
Nouri et al. [37]	Fuzzy Delphi Method, Interpretive structural modelling	hospitality SC	Financial dimension, Supply chain dimension, Stakeholders dimension, Learning, growth and innovation dimension
Nouri et al. [38]	Fuzzy Analytic Hierarchy Process	healthcare sector	Macro Environment Features, Service Provider Features, Supplier Features, Employee Related Features, Customer Features
Sadeghi et al. [14]	factor analysis and fuzzy neural networks	home appliance companies in Iran	Operational Performance (OP), Strategic Performance (SP), Financial Performance (FP), Performance of Information and Communication Technology (PICT),Return Performance (REP), Risk Performance (RIP), Logistic Performance (LP), Market Performance (MP), Internal Structure Performance (PIS) and Growthand Innovation Performance (PGI) , among which, the Strategic Performance (SP) and Return Performance (REP)

III. PROPOSED METHOD

This section presents a new method based on the LS-SVM kernel to create the performance feature and outranking criteria. In this method, we use the comparison matrix to create a set of relationships for outranking. Then, we design the appropriate kernel to create a relevant features space. In the LS-SVM-Ranking method, we generate the best hyperplane in the features space. It has the smallest margin to maintain a comparison matrix relationship. This property will allow the projection on the hyperplane to act as a complete outranking. In this paper we present a new method based on the comparison matrix to provide the output clustering of SVM of a hyperplane to rank the criteria. In the following, we give a brief explanation of leveraged methods.

AHP Method

Suppose $C = \{c_i | i = 1,2,\dots,n\}$ is the set of n considered alternatives. A is a $n \times n$ comparison matrix where $a_{\{i,j\}}$ is the value of alternative i to alternative j.

$$A = \begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,n} \\ a_{2,1} & a_{2,2} & \dots & a_{2,n} \\ \dots & \dots & \dots & \dots \\ a_{m,1} & a_{m,2} & \dots & a_{m,n} \end{pmatrix}$$

$$a_{i,j} \neq 0, a_{i,i} = 1, \quad a_{j,i} = \frac{1}{a_{i,j}}$$

From eigenvalues of A , the largest one is called λ_{max}.

$$A\omega = \lambda_{max}\omega$$

Now the weights (ω) assigned to each alternative in the AHP method are obtained from the eigenvector corresponding to this eigenvalue.

The AHP output highly correlates with the consistency of the pairwise comparisons. The consistency coefficient is defined as:

$$CI = \frac{(\lambda_{max} - n)}{n-1}$$

Finally, the Consistency Ratio (CR) determines that whether the assessments are sufficiently consistent, is defined as follows:

$$CR = \frac{CI}{RI}$$

Random consistency index is the consistency coefficient of a comparative matrix randomly generated by pairwise comparison. If $CR < 0.1$, then comparisons are consistent and acceptable. And if $CR > 0.1$, the ratio values represent inconsistency. In this case, the values of the comparison matrix A should be revised.

Ranking Method

Set of comparative vectors: A set

$$X = \{x_{\{p\}} = (x_p^1, x_p^2, \dots, x_p^m) \mid p = 0,1,\dots,n\}$$

Includes x^p vectors that each vector display a criteria and its components are m performance metric for each criterion which is called a set of comparative vectors.

Ranking function: The function f: X → R is called a ranking or scoring if

$$x_i \succcurlyeq x_j \leftrightarrow f(x_i) \geq f(x_j)$$

It means that criteria x_i is preferred to criteria x_j If and only if the function f is assigned a value greater than x_i.

In the above definition, ranking is expressed as a binary relationship. This is the basis of the ranking in the comparison matrix in the AHP method. Here we examine an overall ranking. Outranking (Roy [63]): The function $f: X \times X \to [0,1]$ is called outranking if:

1. $f(x, x) = 1 \ \forall x \in X$
2. S is increasing in its first argument and decreasing in its second argument.

Global outranking: $f : X \times X \to [0, 1]$ is typically constructed by taking a weighted sum of single-criterion outranking relations $s_k : \cup X \times \cup X \to [0, 1]$:

$$f(x_i, x_j) = \sum_k \omega_k s_k (x_i^k, x_j^k)$$

In the above equation, s_k (x_i^k, x_j^k) is outranking function on the k_t measure performance for all crtiteria, which is a general ranking according to k_t measure performance.

LS-SVM Method

First of all, we explain the general form of the support vector machine, then examine the norm form of SVM, and finally present an outranking based on soft-SVM.

Suppose we have a set of $D = \{(x_1, y_1), (x_2, y_2), \dots (x_N, y_N)\}$ as SVM input where

$$D \subseteq X \times \{1 - ,1\} \mid X \subseteq R^n$$

The set of $Y = \{y_1, y_2, \dots, y_N\}$ will be the set of labels or the output pattern, and the X will be the set of the input pattern data.

The support vector machine is based on creating a hyperplane to separate the pattern data based on the Y data. The separator of data will be the data with the same label as the 1-label data. Hyperplasia will place so that in addition to the distance L_2, its input pattern will be minimized. Hyperplane in the future space is defined as $f = \omega^T X + b$, which ω is the normal vector of the hyperplane. With the given explanations, the LS-SVM form in the hard margin is as follows:

$$minimize \ \frac{1}{2} \parallel \omega \parallel^2$$
$$\omega^T x_k + b \geq 1, \qquad y_k = +1$$
$$\omega^T x_k + b \leq 1, \qquad y_k = -1$$

SVM constraints are abbreviated to $y_k[\omega^T x_k + b] \geq 0$.

Since there is not necessarily a separator Hyperplanes for each input Pattern set, so the constraint of LS-SVM may be empty of answers, so the variable ξ_k is defined so that the LS-SVM constraint is defined:

$$y_k[\omega^T x_k + b] \geq 1 - \xi_k$$

$$\xi_k \geq 0$$

According to the structural risk minimization principle, the Soft (margin) LS-SVM form will be as follows:

$$minimize \quad \frac{1}{2} \parallel \omega \parallel^2 + C \sum_k \xi_k$$
$$y_k [\omega^T x_k + b] \geq 1 - \xi_k$$
$$\xi\_k \geq 0$$

Where C is a constant for the trade-off between the distance of 2- norm of points on the plan which is written in the form *of* $1/2\|\omega\|$ and the pattern error is displayed with $\sum_k \xi_k$.

Kernel LS-SVM Method

The LS-SVM form only includes a linear mode that is, separated by a hyperplane. To create a nonlinear separator (in the three-dimensional space of a surface), we need to define a kernel. Map function from pattern data space to larger space (usually with higher dimension) is defined as:

$$\phi : X \to H$$
$$x \to \phi(x)$$

The ϕ function is called the feature mapping from X to H and H is also called the feature space.

In the context of MCDM, we can think of ϕ as a transformation of the vector of a set of comparative vectors to a new vector with a higher dimension.

Definition of the kernel: function $k: X^2 \rightarrow R$ is called the kernel function whenever the matrix $K = (k\ (x_i, x_j))$ be positive definite. (The matrix K, which its value of (i, j) is a function of $k\ (x_i, x_j)$ and is called the Gram matrix). Feature Space allows us to perform Hyperplane SVM to separate data in the Feature space, which is nonlinear in the X space. The LS-SVM kernel form is as follows:

$$\begin{aligned} &minimize \quad \frac{1}{2} \parallel \omega \parallel^2 + C \sum_k \xi_k \\ &y_k\ [\omega^T\ \phi(x_k)\ +\ b] \geq 1 - \xi_k \\ &\xi_k\ \geq\ 0 \qquad [1] \end{aligned}$$

Using Lagrangian's method and KKT conditions, the Lern-LS-SVM kernel answer, or the hyperplane form in the feature space, will be as follows:

$$f(x) = \sum_i \alpha_i\ y_i\ K\ (x, x_i\ )\ +\ b$$

Where:

$$K(x, x_i) = \phi(x)^T \phi(x_i)$$

And α_i is the answer to the dual Lagrangian problem of kernel LS-SVM.

AHP Kernel LS-SVM Ranking Method

In this section, we present an algorithm based on AHP and Kernel LS-SVM for ranking features. The method consists of three main parts:

1. Data gathering and AHP structure
2. Kernel LS-SVM
3. performance ranking

In the first section, we present a hierarchical structure of indicators. We create a comparative matrix by a set of experts and use AHP to the validation of pairwise comparisons. In this step, if the CR criterion is not appropriate, we repeat the survey step.

In the Kernel LS-SVM step, we first create comparative vectors for the model input and then reach the optimal weights of the ls-svm method by using equation [1]. Finally, in the last step, we will fulfill the overall ranking of the indicators using these weights.

Step 1:

In this step, we will introduce the framework of criteria, suppose $C = \{x_1, x_2, \dots, x_n\}$ is the set of criteria obtained from the evaluation of the AHP method. We obtain the results of the survey by the table from a set of q experts. Suppose $E = \{A_t | t \in [1,2, \dots, q]\}$ is a set of a comparative matrix obtained from q expert, in other words: $A_t = [a_{i,j}]$ is a comparative matrix related to expert t in which the element $a_{i,j}$ is the value of criteria i to j, then we calculate the pairwise comparison matrix A using the geometric mean of the members of E.

The weights of the criteria are calculated from matrix A by the AHP method. Then we calculate the consistency ratio to make sure the quality of the judgment of experts. When $CR \geq 0.1$, we repeat the judgments by the decision team.

Step 2:

At this stage, we construct the resultant comparison vectors corresponding to each pair of indicators from their corresponding members of E. More precisely for two criteria x_i and x_j the comparison vector will be as follows:

$$s(x_i, x_j) = [A_1(i, j), A_2(i, j), \dots, A_n(i, j)] \qquad [2]$$

There are comparative vectors that constitute the input of ls-svm model.

Kernel LS-SVM ranking:

Here the hyperplane function $f = \omega^T\ \phi\ (X)\ +\ b$ is introduced as a ranking that means:

$$x_i \succcurlyeq x_j \leftrightarrow f(x_i) \geq f(x_j)$$

In other words

$$x_i \succcurlyeq x_j \ \leftrightarrow\ \omega^T \left(\phi(x_i) - \phi(x_j)\right) \geq 0 \qquad [3]$$

However, the soft form of the LS-SVM kernel for the above ranking will be as follows:

$$\begin{aligned} &minimize \quad \frac{1}{2} \parallel \omega \parallel^2 + C \sum_k \xi_{i,j} \\ &\omega^T \left(\phi(x_i) - \phi(x_j)\right) \geq 1 - \xi_{i,j} \quad \forall\, x_i \succcurlyeq x_j \\ &\xi_{i,j}\ \geq\ 0 \end{aligned}$$

Step 3:
Comparative vectors as input of Kernel LS-SVM ranking: We put the

$$\Delta\ \phi(x_i, x_j) = \phi(x_i) - \phi(x_j)$$

In the equation [3]:

$$\begin{aligned} &minimize \quad \frac{1}{2} \parallel \omega \parallel^2 + C \sum_k \xi_{i,j} \\ &\omega^T(\delta\phi(x_i, x_j)) \geq 1 - \xi_{i,j} \quad \forall\, x_i \succcurlyeq x_j \\ &\xi_{i,j}\ \geq\ 0 \end{aligned}$$

Also:

$$\Delta f(x_i, x_j) = f(x_i) - f(x_j) = \omega^T(\phi(x_i) - \phi(x_j)) = \omega^T \Delta \phi(x_i, x_j)$$

Δf express the preference of the criteria x_i compared to the criteria x_j.

We equate the differences of the future of the two criteria with the futures of their pairwise comparison:

$$\Delta \phi(x_i, x_j) = \phi(s(x_i, x_j))$$

Remark that ϕ represents the mapping of a q –dimensional real vector $s(x_i, x_j)$ to a feature space.

Solving the above relationship using the Lagrangian method is converted to the following form:

$$L = \frac{1}{2}\|\omega\|^2 + C\sum_{k} \xi_{i,j} - \sum_{i,j} \alpha_{i,j}(\omega^T(\phi(x_i) - \phi(x_j)) - 1 + \xi_{i,j}) + \sum_{i,j} \beta_{i,j}\xi_{i,j}$$

After solving the equations $\frac{\partial L}{\partial \omega} = 0, \frac{\partial L}{\partial \xi_{i,j}} = 0$:

$$\Delta f(x_l, x_k) = \sum_{i,j} \alpha_{i,j} \Delta \phi(x_i, x_j) \Delta \phi(x_l, x_k)$$

That:

$$\alpha_{i,j} = argmax_{\alpha_{i,j}} \sum_{i,j} \alpha_{i,j} - 1/2 \sum_{i,j}\sum_{k,l} \alpha_{i,j}\alpha_{k,l} \Delta \phi(x_i, x_j) \Delta \phi(x_l, x_k)$$

Using the hyperplane obtained from the LS-SVM Ranking method described above, we provide an outranking for criteria. Then, we consider the distance of vectors in the feature vectors into their projection on the hyperplane as criteria for ranking.

$$\text{critria}_i \succcurlyeq \text{critria}_j \leftrightarrow \omega^T\phi(x_i) \geq \omega^T\phi(x_j)$$

In the above relation, $\omega^T \phi(x_i)$ is the distance of $\phi(x_i)$ to hyperplane f, Figure [1]

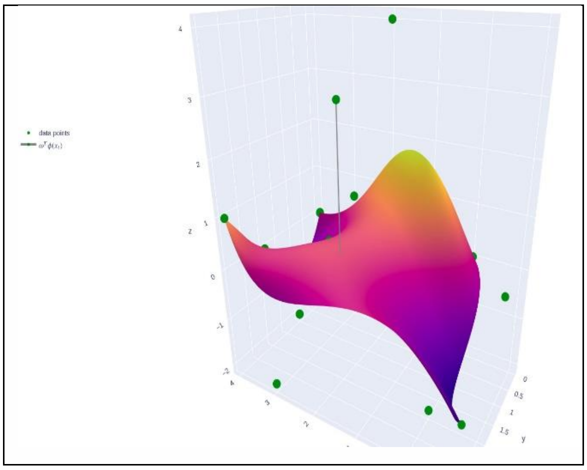

Figure 1. Hyperplane in feature space.

IV. ANALYSIS OF SIMULATION

By expanding IT service providers, the importance of measuring the services of these companies in the field of competition and quality of IT service companies is undeniable.

Based on our previous studies, a set of criteria and alternatives has obtained a hierarchical framework of service measurements in the IT by using a systematic review of literature for articles of the last ten years [64].

We carried out three steps to get the required indicators and framework,

1. Meta Synthesis method: At this stage, out of 133 periodical articles studied, we reached 28 approved articles.
2. CASP method: from the output of stage 1, 15 articles considering the subject scored the lowest quality content analysis, measuring the performance of the service supply chain.
3. Logical model: Finally, to provide a hierarchical (conceptual) framework for providing service supply chain measurement, we presented a logical model categorized into four components: inputs, processes, outputs, consequences.

In Table 2, the corresponding alternatives to the component inputs are classified in the following subindices: Manpower, assets, systems and, technological equipment. In Table 3, the corresponding alternatives to the component internal organizational processes are classified in the following subindices: Demand Management, Capacity and Resource Management, Technology Management, Knowledge and Information Management, Financial and Cash Flow Management, Order Process Management, Service Delivery Management, Risk Management, Developed Programs. In Table 4, the corresponding alternatives to the component ex-organizational processes are classified in the following subindices are classified as Customer Relationship Management (CRM), Supplier Relationship Management (SRM), Mutual Trust. Table 5 provides the corresponding alternatives to the component outputs, in the following subindices are classified: Services provided. Table 6 shows the corresponding alternatives to the component short-term consequences in the following subindices are classified: service quality, financial wealth, competitiveness, customer satisfaction, employee productivity, supplier satisfaction, level of buyer, and supplier participation, information quality, regulatory compliance. Finally, in Table 7, the corresponding alternatives to the component; Long-term consequences (environmental impact): in the subindices of environmental service operations design, cost control, green activities, environmental friendliness, waste management are classified.

TABLE II. SHOWS COMPONENT INPUTS ARE CLASSIFIED BY THE CORRESPONDING ALTERNATIVES SUBINDICES.

Inputs	Performance metrics	Index
Manpower	number of employees	C1
	knowledge and skills	C2
Assets	total assets	C3
Systems and Technological Equipment	Customer relationship system	C4
	Supplier Communication System	C5
	Management information system(MIS)	C6
	Security service management system(ITIL)	C7
	Electronic and non-electronic record management system	C8
	Security and safety systems(WAF/IDS,...)	C9
	Decision support system(DSS)	C10
	Human resource management system	C11
	Physical protection system	C12
	The ratio of active technologies in the field of service management to the whole technology	C13

Finally, our IT case includes 120 major performances measure, the criteria measurement classified into 6 general indicators. We used a team of ten IT experts and obtaining the Kendalls coefficient of concordance 0.742, among the experts. The results are shown in Tables (1 to 6). To construct the E comparison matrix, we used the matrix of the AHP method, and the rows of the matrix were created to form a set of relations $x_i \succcurlyeq x_j \cong x_i^j \in X$ based on the E_r comparison matrix.

To implement the AHPKernel LS-SVMRanking method (AHP-KLS-SVM Ranking), we used the Cornell University SVMlight Library [62]. For this purpose, we convert the input sample to libsvm format, this format is

$$< qid: label_j, lable_1: value_1, lable_2: value_2, .., \\ lable_{120}: value_{\{120\}} > \ where \ lable_i$$

represents the index of i −th measurement and $value_i$ represents the ratio of the j-th measurement to the i-th that we have stored in matrix E.

We used Python 3 to generate the required input in libsvm format and use SVM light, which is written in C language. In this method, we use the comparison matrix obtained from each expert as a query to train the AHP-KLS-SVM Ranking algorithm. After learning the AHP-KLS-SVM Ranking algorithm, the output of hyper Surface weights in linear kernel mode and the ϕ surface coefficients in Gaussian kernel is seen. The output weights are shown in Tables 8 and 9. We have compared the output rankings of these two kernels with the AHP method in Tables 8 and 9. The results obtained in Figure 2 are compared, which shows the ranking chart of the indicators in all three methods.

V. CONCLUSIONS AND FUTURE WORK

This paper presented a hybrid method based on AHP and SVM for ranking the service supply chain criteria. In this paper, we introduced the framework of IT service chain criteria and used AHP to test the experts' judgments. Afterward, the relationship between criteria, which have been acquired from the experts, constructs the input of the SVM-ranking model.

Figure 2. Results in the linear kernel (AHP-KLS-SVM), Gaussian kernel (AHP-KLS-KSVM), and AHP ranking.

Compared to previous outranking machine learning methods, including SVM-based methods, the AHP Kernel LS-SVM Ranking method, presented in this paper, is able to provide single-level and multi-level frameworks of criteria with outranking. In this method, create a comparison matrix using AHP, it is possible to create high-dimensional vectors to display the value of each indicator in all criteria so that it can be a suitable input for the Kernel LS-SVM Ranking method.

If the framework is one-level, the input of SVM ranking in previous methods will be one-dimensional, and the comparison will not include all the criteria in this algorithm. Also, presenting the kernel method of LS-SVM Ranking, provide higher accuracy surface for an average of data, and use the closeness criterion for outranking, which in LS-SVM Ranking mode, only one hyperlink can be passed through the data. There was, and this allows for accuracy in the high number of indicators. The machine learning method, in addition to the stated accuracy, can also be applied in the mode of criterion and increase the opinions of experts to analyze the opinions of ordinary users. While the previous methods for this purpose are slow at runtime.

In our model, the results show a higher speed. Additionally, in AHP methods, the spaces of eigenvectors create a criterion for checking performance and overall ranking. The projection function ϕ , in the futures space can create a linear space or a surface in the upper dimension, and the projection function on this surface forms the ranking. In this method, the consequence of experts' opinions is applied for ranking, which is an improvement over the SVM Ranging method.

TABLE III. CORRESPONDING ALTERNATIVES TO THE COMPONENT "INTERNAL ORGANIZATIONAL PROCESSES" ARE CLASSIFIED BY SUB-INDICES.

Internal	**Performance metrics**	**Index**
Demand Management	Ability to estimate demand	C14
	Allocation planning	C15
Capacity and Resource Management	Optimal use of capacity and resources	C16
	Ability to determine service capacity	C17
	Staff training and participation	C18
	Staff promotion based on capacity building	C19
Technology Management	Decision making based on the latest information technologies	C20
	Ability to provide technical performance on a daily basis	C21
	Evaluate up-to-date and modern technologies to upgrade them	C22
Knowledge and Information Management	Ability to share new information and knowledge electronically with partners	C23
	Ability to quickly access accurate and up-to-date information at any time (via information technology	C24
	Support the implementation of knowledge management mechanisms at the chain level	C25
Financial and Cash Flow Management	Ability to pay damages (in the form of SLA)	C26
	Apply optimization methods of service tariff	C27
Order	Efficient order management mechanism (fast and accurate order processing)	C28
Process Management	Ability to simplify the service ordering process (for example, receiving orders electronically or submitting in SLA format	C29
	Share up-to-date information on customer order status with partners	C30
Service Delivery Management	Ability to provide service catalogs	C31
	Ability to provide tracking code for orders	C32
	Service order delay time	C33
	Ability to deliver standard services	C34
	Ability to perform accurate and reliable service process	C35
	Evaluate service delivery performance compared to competitors according to customer feedback	C36
	Ability to improve the process and technical delivery of services	C37
	Service delivery delay time	C38
Risk Management	Ability to identify risks and determine the severity of their consequences	C39
	Design the right response to the risks	C40
	Ability to create coordination among members to reduce supply chain vulnerabilities	C41
	Ability to review threatening factors at appropriate and preferably specified time intervals	C42
	Ability to manage supply chain problems (service delivery)	C43
	Risk management based on security services management system or observance with the standards of this category	C44
Developed Program	Strategic planning (for organizational sustainability)	C45
	IT application software	C46
	Growth and learning programs for stakeholders	C47

The results show that in our method, knowledge and skills, management information system, security service management system, ability to communicate effectively with the customer, ability to establish effective relationships with suppliers, the performance of provided services, and customer response time criteria are the most important among 112 examined criteria. As a result, more attention to them caused a significant increase in the quality of measuring the performance of companies.

TABLE IV. THE CORRESPONDING ALTERNATIVES TO THE COMPONENT EX-ORGANIZATIONAL PROCESSES ARE CLASSIFIED.

ex-organizational	**Performance metrics**	**Index**
Customer Relationship Management (CRM)	Techniques for continuous process improvement	C48
	Complaints management	C49
	Ability to communicate effectively with the customer	C50
	Ability to customize customer requests	C51
	Ability to categorize and prioritize key customers	C52
	Ability to measure the quality of customer relations	C53
Supplier Relationship Management (SRM)	Ability to establish effective relationships with suppliers	C54
	Ability to focus on key suppliers	C55
	Ability to create collaborative partnerships with suppliers by sharing information	C56
	Anticipate alternative routes to meet key needs	C57
Mutual Trust	Transparency of contracts	C58
	Credibility of cooperation	C59
	Profit-sharing	C60

TABLE V. CORRESPONDING ALTERNATIVES TO THE COMPONENT SHORT-TERM CONSEQUENCES IN THE FOLLOWING SUB-INDICES.

Outputs	Performance metrics	Index
Services	Type / scope of services provided(B2B/B2C/B2G)	C61
provided	Service delivery capacity	C62

TABLE VI. CORRESPONDING ALTERNATIVES TO THE COMPONENT THE SUB-INDICES.

Short-term Sequences	Comperformance metrics	Index
Service quality	Variety of services	C63
	Total service cycle time	C64
	Performance of provided services	C65
	The physical condition of the provided services	C66
	Reliability of services (in the form of SLA)	C67
	Service flexibility (volume, speed, delivery time, specifications, customer needs)	C68
Financial Wealth	Profitability	C69
	The total cost of service delivery	C70
	Investment (by the government)	C71
	Debt to assets ratio	C72
	Return on Investment Rate (ROI)	C73
	Total time flow of funds	C74
Competitiveness	Attract new customers	C75
	Service innovation	C76
	Sales network efficiency	C77
	Market share development (domestic market share and foreign market share)	C78
	Providing new and up-to-date technologies to the world	C79
Customer Satisfaction	Costomer loyalty	C80
	Empathy with the customer	C81
	Promise to the customer	C82
	Customer response time	C83
employee productivity	Quality of employee’s work	C84
	Employee response speed	C85
	Employee loyalty	C86
	Employee satisfaction	C87
	Employee turnover	C88
	Staff turnover rates	C89
Supplier Satisfaction	Quality of service level suppliers	C90
	Speed suppliers	C91
	Commitment of suppliers	C92
	Supplier pricing versus market	C93
Level Of Buyer and Supplier Participation	Level and amount of information exchange	C94
	The degree of mutual cooperation for continuous improvement	C95
	Mutual understanding and closeness for business growth long- term perspective	C96
Information Quality	Accuracy of information exchanged	C97
	Adequacy of information (comprehensiveness, accuracy, appro- privateness)	C98
	Confidentiality and security of information	C99
Regulatory	Observance of rules and standards	C100
Compliance	Adherence to the program	C101

TABLE VII. THE CORRESPONDING ALTERNATIVES TO THE COMPONENT.

Long-term Sequences	con- Performance metrics	Index
Environmental Service	Identify, monitor and, review standard deviations in compliance with the rules	C102
Operations	Environmental certifications	C103
Design	Assessing the social impact of business by the environment	C104
Cost Control	Costs of environmental improvement (elimination of air pollution, etc.)	C105
Green Activities	Use of environmentally friendly technologies	C106
	Awareness of environmental protection	C107
	Maintaining the health and safety of customers and employees	C108
Environmental	Environmental information systems	C109
Friendliness	Green management system	C110
Waste Management are Classified	Recycling, reuse and disposal	C111
	Reverse logistics integration in services	C112

TABLE VIII. SHOWS COMPARED THE OUTPUT RANKINGS OF THESE TWO KERNELS WITH THE AHP METHOD.

Index	AHP-KLS-SVM (linear kernel)	AHP-KLS-SVM(Gaussian kernel)	FAHP
C1	2.64002406	15.61270171	0.00192973
C2	4.40004006	9.4308062	0.0260742
C3	2.64002406	15.61270171	0.00200645
C4	3.52003209	12.28477912	0.01825837
C5	3.52003209	12.28477912	0.01063117
C6	4.40004006	9.4308062	0.01002162
C7	4.40004006	9.4308062	0.00519264
C8	2.64002406	15.61270171	0.00477119
C9	1.76001604	19.2002816	0.00744765
C10	3.52003209	12.28477912	0.00670325
C11	0.88000802	22.78828738	0.00258144
C12	0.88000802	22.78828738	0.00347377
C13	1.76001604	19.2002816	0.00369629
C14	3.52003209	12.28477912	0.00950148
C15	2.64002406	15.61270171	0.00861948
C16	3.52003209	12.28477912	0.00758953
C17	0.88000802	22.78828738	0.00212634
C18	3.52003209	12.28477912	0.01002162
C19	2.64002406	15.61270171	0.00299285
C20	1.76001604	19.2002816	0.00839715
C21	2.64002406	15.61270171	0.0029369
C22	2.64002406	15.61270171	0.00312658
C23	3.52003209	12.28477912	0.00861948
C24	3.52003209	12.28477912	0.0129579
C25	2.64002406	15.61270171	0.00701623
C26	3.52003209	12.28477912	0.0039188
C27	2.64002406	15.61270171	0.00326264
C28	4.40004006	9.4308062	0.005331
C29	3.52003209	12.28477912	0.0077487
C30	2.64002406	15.61270171	0.00615545
C31	2.64002406	15.61270171	0.00463056
C32	3.52003209	12.28477912	0.00347377
C33	4.40004006	9.4308062	0.00714989
C34	4.40004006	9.4308062	0.01247779
C35	4.40004006	9.4308062	0.02351498
C36	3.52003209	12.28477912	0.02101252
C37	3.52003209	12.28477912	0.00495469
C38	3.52003209	12.28477912	0.01151441
C39	3.52003209	12.28477912	0.02046963
C40	4.40004006	9.4308062	0.02351498
C41	4.40004006	9.4308062	0.02301891
C42	2.64002406	15.61270171	0.0112991
C43	3.52003209	12.28477912	0.01403462
C44	3.52003209	12.28477912	0.01440646
C45	2.64002406	15.61270171	0.0023419
C46	2.64002406	15.61270171	0.00369629
C47	2.64002406	15.61270171	0.00558704
C48	3.52003209	12.28477912	0.00281096
C49	3.52003209	12.28477912	0.00627271
C50	4.40004006	9.4308062	0.01751544
C51	4.40004006	9.4308062	0.01605413
C52	3.52003209	12.28477912	0.00895106
C53	3.52003209	12.28477912	0.00929541
C54	4.40004006	9.4308062	0.01932251
C55	3.52003209	12.28477912	0.01351459
C56	2.64002406	15.61270171	0.00593055

TABLE IX. SHOWS COMPARED THE OUTPUT RANKINGS OF THESE TWO KERNELS WITH THE AHP METHOD.

Index	AHP-KLS-SVM (linear kernel)	AHP-KLS-SVM (Gaussian kernel)	FAHP
C57	3.52003209	12.28477912	0.01106694
C58	3.52003209	12.28477912	0.01247779
C59	2.64002406	15.61270171	0.00558704
C60	2.64002406	15.61270171	0.00422364
C61	2.64002406	15.61270171	0.01043239
C62	3.52003209	12.28477912	0.01998934
C63	2.64002406	15.61270171	0.01224445
C64	3.52003209	12.28477912	0.0178493
C65	4.40004006	9.4308062	0.02175728
C66	2.64002406	15.61270171	0.00312658
C67	3.52003209	12.28477912	0.01714617
C68	2.64002406	15.61270171	0.01825837
C69	3.52003209	12.28477912	0.00627271
C70	3.52003209	12.28477912	0.00800742
C71	2.64002406	15.61270171	0.00326264
C72	3.52003209	12.28477912	0.0024995
C73	3.52003209	12.28477912	0.005331
C74	3.52003209	12.28477912	0.00166368
C75	0.88000802	22.78828738	0.00410692
C76	3.52003209	12.28477912	0.01825837
C77	3.52003209	12.28477912	0.00438088
C78	2.64002406	15.61270171	0.01605413
C79	3.52003209	12.28477912	0.01567765
C80	3.52003209	12.28477912	0.00670325
C81	4.40004006	9.4308062	0.00438088
C82	4.40004006	9.4308062	0.01195743
C83	4.40004006	9.4308062	0.01440646
C84	2.64002406	15.61270171	0.0039188
C85	4.40004006	9.4308062	0.00580192
C86	4.40004006	9.4308062	0.00714989
C87	4.40004006	9.4308062	0.00477119
C88	3.52003209	12.28477912	0.00361839
C89	2.64002406	15.61270171	0.00651397
C90	3.52003209	12.28477912	0.00977438
C91	4.40004006	9.4308062	0.01538443
C92	3.52003209	12.28477912	0.01440646
C93	3.52003209	12.28477912	0.0129579
C94	3.52003209	12.28477912	0.00895106
C95	3.52003209	12.28477912	0.01063117
C96	2.64002406	15.61270171	0.00326264
C97	3.52003209	12.28477912	0.02253331
C98	3.52003209	12.28477912	0.01605413
C99	2.64002406	15.61270171	0.01173383
C100	2.64002406	15.61270171	0.00509557
C101	3.52003209	12.28477912	0.00800742
C102	3.52003209	12.28477912	0.0028645
C103	0.88000802	22.78828738	0.00135148
C104	0.88000802	22.78828738	0.00219472
C105	0.88000802	22.78828738	0.00174717
C106	1.76001604	19.2002816	0.00219472
C107	0.88000802	22.78828738	0.00154428
C108	2.64002406	15.61270171	0.01351459
C109	0.88000802	22.78828738	0.00182658
C110	0.88000802	22.78828738	0.00178444
C111	1.76001604	19.2002816	0.00240105
C112	2.64002406	15.61270171	0.00101294

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